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Characterization of Superalloys by Artificial Neural Network Method

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Abstract: In this study, the use of artificial neural networks in the classification of a superalloys whose chemical analysis is performed in the quality process is investigated. In general, chemical spectro analysis method alone is not sufficient to determine which class a steel belongs to. In addition to the chemical analysis method, tests such as tensile test, hardness test or notch impact test are applied. The tests performed in addition to the chemical analysis both take time and destroy the material. The fact that an algorithm that classifies steel only according to the results of chemical analysis is not used has made destructive tests mandatory. Artificial neural networks (ANNs), usually simply called neural networks (NNs), are computing systems inspired by the biological neural networks that constitute animal brains. An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit a signal to other neurons. In our study, a total of 34 superalloy materials belonging to 6 different classes were used. Chemical composition values were determined for each superalloy sample. The appropriate artificial neural network model was determined according to the chemical composition values. A model that can predict superalloy material based on chemical composition value has been created. Weka 3.9.5 package program was used to create the artificial neural network model. The high success rate of the prediction model gave hope for the determination of the material class only with the chemical analysis method.

Keywords: Superalloy, Artificial Neural Networks, Weka, Chemical Composition

1 Introduction

The aim of this study is to classify superalloys according to their chemical composition by artificial neural network method. Superalloys are a type of alloy based on the 8B elements in the periodic table [1]. They are obtained by mixing various combinations of Fe, Ni, Co and Cr. In addition to the main alloying elements, there are elements such as W, Mo, Ta, Nb, Ti and Al in superalloys [2]. Element ratios in superalloys are the main classification criteria of superalloys. In a quality control laboratory, it is possible to determine the chemical composition of an alloy whose content is unknown by a method such as spectro analysis. In determining the classification of superalloys or any steel alloy, it is often not sufficient to know the chemical compositions alone [3]. For different types of superalloys, the percentage weight ratios of many elements are not strictly separated from each other [4]. A quality control engineer interpreting chemical analysis results often needs a second or third test method to support the results. Although the chemical analysis method is the main factor in determining the type of superalloys, it cannot be decisive in the quality control method. The reason for this is that adequate algorithms have not been established for the determination of material type according to chemical composition. In this study, it was studied on the material characterization of superalloys with the artificial neural network method [5]. Artificial neural networks are information processing technology that works by imitating the working principle of the human brain. It is based on digital modeling of biological neuron cells and the synaptic link established by these cells with each other [6]. Learning process in artificial neural networks is carried out using examples. During learning, input and output information is given and rules are set. Thanks to artificial neural networks, we can easily enable the system to

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learn from thousands of samples, both desirable and undesirable. In this study, it is aimed to predict superalloy material characterization by taking advantage of the learning ability of artificial neural networks.

2 Material and Method

2.1 Determination of Superalloy Samples

Superalloys are divided into 3 main groups: Iron-based superalloys, nickel-based superalloys, cobalt-based superalloys. They are divided into various classes within themselves in 3 main groups. According to the manufacturing method, we can divide superalloys into 6 as wrought, sx, deposited, MA/ODS, cast and PM. In our study, a total of 34 samples obtained with these 6 manufacturing methods were studied as shown Table 1. The weight ratios of 15 different elements in the content of 34 superalloy materials were included in the evaluation are shown Table 2.

	Superalloys	Number of samples
1	Wrought	12
2	SX	15
3	Deposited	1
4	MA/ODS	4
5	Cast	1
6	PM	1

Table 1: Superalloys samples types

Elements														
Cr	Co	Mo	W	Ta	Nb	Al	Ti	Fe	C	B	Zr	Re	Hf	Ru

Table 2: Elements of Superalloys

In our study, 34 samples were used in a total of 6 groups whose chemical analysis results were known, and the data were obtained from open source www.kaggle.com.

2.2 The propagation of the shallow water waves problem

In practical terms neural networks are nonlinear statistical data modeling tools [7]. They can be used to model complex relationships between inputs and outputs or to find patterns in data [8]. Using neural networks as a tool, data warehousing firms are harvesting information from datasets in the process known as data mining [9]. In this research we have used Weka for the entire implementation. Simple training and testing using multilayer perceptron neural network was done first. For this the entire data set was divided into two separate tests. Training was done by adjusting the different learning and momentum rates. Among the training results the best was taken for analysis. Second MLP training after association rule mining is done. Association rule mining extracts the important rules so that it helps to identify the important attributes [10]. In this study, the multilayer Perceptron system was used. Multilayer Perceptron (multilayer sensors) is a sensor system consisting of three layers.
There are 3 layers called input layer, hidden layer and output layer [11]. As seen in Figure 1, a total of three-layer artificial neural network model with 2 hidden layers was used in our study as a result of the experiments [12].

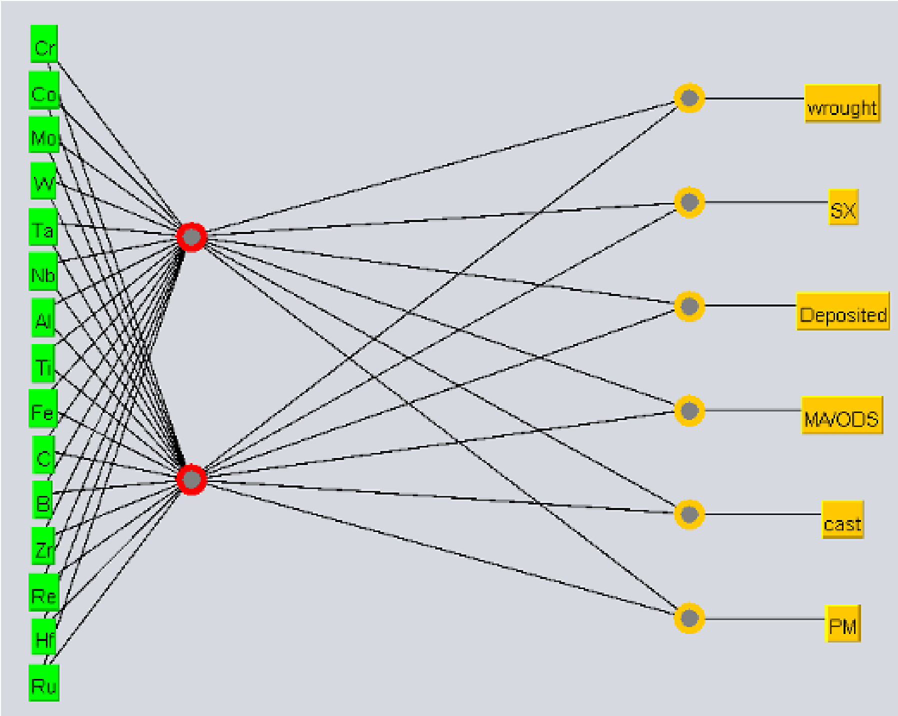

Fig. 1: The structure of Multilayer Perceptron

3 Result

The following values were obtained as a result of modeling with artificial neural networks. Confusion matrix was used to determine the error rates and the values are shown in the Table 4.

a	b	c	d	e	f	
10	1	0	1	0	0	a=Wrought
1	14	0	0	0	0	b=SX
1	0	0	0	0	0	c=Deposited
0	0	0	4	0	0	d=MA/ODS
1	0	0	0	0	0	e=Cast
0	1	0	0	0	0	f=PM

Table 4: Confusion Matrix

5 of the most important formulas in determining the success rates of artificial neural networks are shown in table 5. The success rate of the established model was interpreted according to the values of Mean Absolute Error-MAE, Root Mean Squarred Error-RMSE, Relative Absolute Error-RAE, Root Relative Squarred Error-RRSE, Correctly Classified Instances.

No	Type	Cr	Co	Mo	W	Ta	Nb	Al	Ti	Fe	C	B	Zr	Re	Hf	Ru
1	Wrought	14,5	20	5	0	0	0	0	1,2	4,5	0	0,2	0	0	0	0
2	Wrought	15	18,5	5,2	0	0	0	4,3	3,5	0	0,08	0,03	0	0	0	0
3	Wrought	15,5	0	14,5	0	0	0	0,2	0	1	0,02	0,01	0	0	0	0
4	Wrought	15,8	0	0	0	0	0	0	0	7,2	0,04	0	0	0	0	0
5	Wrought	18	18,5	4	0	0	0	2,9	2,9	0	0,08	0,01	0,05	0	0	0
6	Wrought	18,6	0	3,1	0	0	5	0,4	0,9	18,5	0,04	0	0	0	0	0
7	Wrought	19	9	2,8	1,1	0	5,6	1,45	0,75	9	0,03	0,01	0	0	0	0
8	Wrought	19	11	10	0	0	0	1,5	3,1	0	0,09	0,05	0	0	0	0
9	Wrought	19,5	1,1	0	0	0	0	1,3	2,5	0	0	0,06	0	0	0	0
10	Wrought	19,5	13,5	4,3	0	0	0	1,3	3	0	0,08	0,01	0,06	0	0	0
11	Wrought	20	0	0	3,5	0	0	2,3	2,1	5	0,07	0,01	0	0	0	0
12	Wrought	22	1,5	9	6	0	0	0	0	18,5	0,1	0	0	0	0	0
13	SX	2	3	0,4	5	8	0,1	5,7	0,2	0	0	0	0	6	0,03	0
14	SX	2,3	3,3	0,4	5,5	8,4	0	5,8	0,2	0	0	0	0	6,3	0,03	0
15	SX	2,3	6	1,5	7	8,4	0	5,8	0,2	0	0	0	0	6,3	0,03	2
16	SX	2,3	6	3	6	8,4	0	5,8	0,2	0	0	0	0	6,3	0,03	6
17	SX	2,9	5,8	3,9	5,8	5,6	0	5,8	0	0	0	0	0	4,9	0,1	6
18	SX	3	12	2	6	6	0	0	0	0	0	0	0	5	0,1	0
19	SX	3	12	3	6	6	0	0	0	0	0	0	0	5	0,1	2
20	SX	4,2	12,5	1,4	6	7,2	0	5,75	0	0	0	0	0	5	0,15	0
21	SX	5,7	11	0,42	5,2	5,6	0	5,2	0,74	0	0	0	0	3	0,1	0
22	SX	6,9	0	7,5	0	8,4	0	5,8	0	0	0	0	0	0	0	0
23	SX	7	8	2	5	7	0	6,2	0	0	0	0	0	3	0,2	0
24	SX	8	4,6	0,6	7,9	5,8	0	5,6	0,9	0	0	0	0	0	0	0
25	SX	8,5	5	0	9,5	2,8	0	5,5	2,2	0	0	0	0	0	0	0
26	SX	9,8	5	3	0	2,1	0	4,8	4,7	0	0	0	0	0	0	0
27	SX	10	15	3	0	0	0	0,05	4	0	0	0	0	0	0	0
28	Deposited	22	0,1	9	0	0	3,5	0,1	0,2	3	0,01	0	0	0	0	0
29	MA/ODS	15	0	0	3,9	0	0	4,5	2,3	1,5	0,06	0	0	0	0	0
30	MA/ODS	19,5	0	0	3,4	0	0	6	0	1,2	0,06	0	0	0	0	0
31	MA/ODS	20	0	0	0	0	0	0,3	0,5	3	0	0	0	0	0	0
32	MA/ODS	30	0	0	0,5	0	0	0,3	0	0	0,05	0	0	0	0	0
33	Cast	9	10	0	12	0	1	5	2	0	0,15	0,02	0,05	0	0	0
34	PM	14,9	17,2	5,1	0	0	0	4	3,5	0	0,03	0	0,04	0	0	0

Table 3: Dataset of Superalloys Samples

Mean Absolute Error-MAE	$MAE = \frac{1}{n}\sum_{i=1}^{n}\lvert y_i - \hat{y}_i\rvert$	0,1011
Root Mean Squared Error-RMSE	$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{n}}$	0,2382
Relative Absolute Error-RAE	$RAE = \sum_{i=1}^{n}\frac{\lvert e_i\rvert}{y_i-\hat{y}_i}$	43,365 %
Root Relative Squared Error-RRSE	$RRSE = \sqrt{\sum_{i=1}^{n}\frac{\lvert e_i^2\rvert}{(y_i-\hat{y}_i)^2}}$	70,5381 %
Correctly Classified Instances	Accuracy=$\frac{TN+TP}{TP+TN+FP+FN}$	82.35%

Table 5: Criterion Functions

4 Discussion

In this study, artificial neural network method is used for superalloy determination consisting of 6 samples. There are a total of 16 elements in the samples of the super alloy test samples. While some of the alloying elements are present in more than one test sample, some elements are not found in superalloys. Many attempts have been made to obtain the optimum result in ANN modelling. A total of three-layer artificial neural networks model was used to determine the type of superalloy with known chemical composition. As a result of the ANN model, 82.35% correctly classified instances were found. This study, which was made with a limited number of samples in superalloys, made highly accurate modeling. t has given hope that models with a high percentage of accuracy can be created by increasing the number of samples and improving the model. With the development of the model, it has been concluded that superalloy classifications are possible only by chemical analysis methods without damaging the material in the quality control processes of superalloys.

Competing interests

The authors declare that they have no competing interests.

Authors' contributions

All authors have contributed to all parts of the article. All authors read and approved the final manuscript.

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